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Regulators as agents: Modelling personality and power as evidence is brokered to support decisions on environmental risk

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HIGHLIGHTS

- The role of personality and power in regulatory decision-making is poorly represented.
- We built a rudimentary two-agent model to explore environmental risk decisions.
- Our two agent model accounted for decisions about the sufficiency of evidence.
- We examined the influence personality and power has on confidence gained.
- By giving agents personality we might predict the time taken to reach consensus.

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ABSTRACT

Complex regulatory decisions about risk rely on the brokering of evidence between providers and recipients, and involve personality and power relationships that influence the confidence that recipients may place in the sufficiency of evidence and, therefore, the decision outcome. We explore these relationships in an agent-based model; drawing on concepts from environmental risk science, decision psychology and computer simulation. A two-agent model that accounts for the sufficiency of evidence is applied to decisions about salt intake, animal carcass disposal and radioactive waste. A dynamic version of the model assigned personality traits to agents, to explore their receptivity to evidence. Agents with 'aggressor' personality sets were most able to imbue fellow agents with enhanced receptivity (with 'avoider' personality sets less so) and clear confidence in the sufficiency of evidence. In a dynamic version of the model, when both recipient and provider were assigned the 'aggressor' personality set, this resulted in 10 successful evidence submissions in 71 days, compared with 96 days when both agents were assigned the 'avoider' personality set. These insights suggest implications for improving the efficiency and quality of regulatory decision making by understanding the role of personality and power.

1. Introduction

Complex regulatory decisions on risk rely on the provision, scrutiny and acceptance of scientific evidence. Davies et al. (2010) explain how evidence is brokered (received, processed and passed on) between actors – a regulatee and regulator for example – in order to assess the significance of risks and inform decisions on how they should be managed (Oxera, 2000). As evidence is exchanged between organisations and promoted through a decision hierarchy towards the ultimate decision maker, intermediate recipients judge the sufficiency of evidence for those aspects of the decision they are accountable for. Only when deemed sufficient is evidence passed on to others for a similar interrogation. In regulatory settings, the recipients of evidence may also hold and exercise power over the provider with respect to its sufficiency. As a contribution to the smarter regulation debate (Better Regulation Commission, 2006; Gouldson et al., 2009; Hutter, 2005; Taylor et al., 2012, 2013) we are interested in how regulatory confidence in risk-informed decisions is instilled as evidence is brokered between parties. We suggest that agent-based tools may help researchers explore relationships between evidence, personality and power (Davies et al., 2010). Here, we describe a research tool for this purpose and test its applicability in the complex environment of regulatory decision-making using three case studies.

Agent-based modelling simulates the relationships between actors participating in complex decisions (Courdier et al., 2002; Chaturvedi et al., 2000; Kurahashi and Terano, 2005). It has been used in the

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environmental sciences to explore negotiations on groundwater management (Feuillette et al., 2003), the effectiveness of greenbelt allocation in periurban settings (Brown et al., 2004), forest management strategies (Nute et al., 2004) and pine beetle infestation (Perez and Dragicevic, 2010). By combining knowledge about choice, so-called 'automated decision makers' can partially represent human interactions by accounting for the behaviours and makeup of actors. Using these tools, scholars have modelled the influence of personality (a factor of individual difference; Alavizadeh et al., 2008; Canuto et al., 2005; Ghasem-Aghaee and Ören, 2007; Nassiri-Mofakham et al., 2008, 2009) and power (a factor of the interactions between individuals; Cincotti and Guerci, 2005; Marreiros et al., 2008; Prada and Paiva, 2009) on decision making.

Applications that explore how agents broker scientific evidence between one another are limited (Chen et al., 2001; Berger et al., 2010). Scholars have, however, simulated the effectiveness of trading agents (Haddawy et al., 2004), investigating the effectiveness of auctions (Bohte et al., 2001; Mizuta and Steiglitz, 2000; Mizuta and Yamagata, 2001), buyer coalition schemes (Yamamoto and Sycara, 2001) and trade brokering (Alkemade et al., 2003). Agents mimic brokering by representing an exchange of information between parties to a decision. In models of financial trade, analogous here to the exchange of evidence, agents are the buyers and sellers of a commodity. Successful trades demonstrate small fluctuations over time. In regulatory decision-making, a recipient of evidence (usually the regulator) who gives positive feedback to the provider of evidence (the regulatee, operator) might increase the provider's understanding of what is expected of a regulatory submission (e.g. an environmental safety case). This may mean fewer fluctuations in the recipient's view about the sufficiency of the evidence submitted, with a possibility for smoother regulatory approvals as an outcome for both parties — a successful 'trade' of evidence and increased confidence on behalf of the recipient. Conceptualising the role of receptivity about knowledge is not new. Both knowledge creation and transfer are dependent on transparency and receptivity (Larsson et al., 1998), some claiming these as key to building trust (McCole, 2002), to effective communication (Tsai et al., 2008) and as determinants of inter-partner learning (Hamel, 1991). In short, establishing interpersonal relations through receptivity and transparency encourages the free flow of information (Tsai et al., 2008).

Bringing the features of real-world regulatory decisions on risk, personality and power together within an agent-based model are challenging and we are cautious about claims to reproduce the complexities of multi-agent decisions. Arthur (1999) comments on the reality of economics via-à-vis our attempts to model the flows and interactions between agents:

> "*[…] the economy itself emerges from our subjective beliefs. These subjective beliefs, taken in aggregate, structure the micro economy. They give rise to the character of financial markets. They direct flows of capital and govern strategic behaviour and negotiations. They are the DNA of the economy. These subjective beliefs are a-priori or deductively indeterminate in advance. They co-evolve, arise, decay, change, mutually reinforce, and mutually negate. Subject and object cannot be neatly separated. And so the economy shows behaviour that we can best describe as organic, rather than mechanistic. It is not a well-ordered, gigantic machine. It is organic. At all levels it contains pockets of indeterminacy. It emerges from subjectivity and falls back into subjectivity.*"

Modestly, we are concerned with whether relationships between evidence, people (personality) and power (structures) can be represented in an agent-based model to examine regulatory decisions: (i) can we construct such a model?; (ii) can it represent power structures and information flows?; (iii) can we represent the influence of personality traits and decision context on decision outcome? We explore these questions in a two-agent model incorporating the prior art on power (French and Raven, 1959) and personality (Costa and McCrae, 1992) alongside expert knowledge captured from case study interviews.

2. Methods and model development

A proof of concept model was designed by reference to three case studies from Davies et al. (2010). The flow of evidence between parties to these decisions (regulatees, their professional advisors, regulators and their advisors, the final decision-maker) was mapped according to Oxera (2000). A two-agent model was then designed to represent the receptivity of recipients (the regulator) to the evidence submitted by a provider (the regulatee, or operator). Having tested its functionality, a dynamic version of the model was attempted, accounting for receptivity between parties and, by inference, the degree of recipient confidence in the evidence brokered to inform risk decisions.

2.1. Scoping study — characterising the brokering of evidence

Prior to model design, open-ended interviews (n = 5) were conducted with regulators to obtain generalised insights on the brokering of evidence in regulatory decision-making. The researcher (GJD) assured confidentiality before recording interviews, asking respondents to explain their expert role and the brokering process. Interviews revealed the real-life complexities that characterise the flow of information within decisions, which are not represented in decision diagrams or risk frameworks. Field notes and interviews were transcribed and used to support development of lengthier semi-structured interviews and the agent-based model described below.

2.2. Case study selection and decision routes

The research utilised three of six candidate case studies. These three were chosen because they reflected a range of conditions for the brokering of evidence (Table 1) and provided access to willing participants: (1) the regulatory review of a post-closure safety case for low-level nuclear waste disposal (denoted NW; an environmental permitting decision); (2) the disposal of avian influenza infected animal carcasses (AI; a planning decision under emergency conditions) and (3) the proposal to reduce levels of dietary salt intake (SI; a policy development decision).

Evidence in the NW case study passes through a well-defined decision framework and embodies high levels of scientific uncertainty, given the need to examine radioactive releases to the biosphere over geological time. In contrast, the SI case study involved relatively undisputed evidence about harm, but uncertainty around the optimal policy intervention required to manage risk. The AI case study was concerned with an emergency response where the evidence being

Table 1
Six candidate case studies (shaded ones selected) with decision attributes.

	Novelty	Scientific uncertainty	Bureaucratic structure	Environmental planningcontext	Policy development	Operational/tactical regulation	Flexibility of decision framework	Public dread	Emergency response	Geographically disperse
1. Risk associated with the disposal of infected animal carcasses (AI)	X			X					X	
2. Risk a ssociated with the dietary saltintake (SI)					X		X			X
3. Risk associated with nuclear waste disposal (NW)		X	X			X		X		
4. Risk associated with an outbreak of blue-tongue disease	X	X				X			X	
5. Risk associated with seasonal flooding				X					X	X
6. Risk associated with the disposal of hazardous waste to landfill		X	X			X				

brokered was for emergency planning purposes in anticipation of relatively 'novel' risks. For each case study, peer reviewed and grey literature was used to inform the directional flow of evidence and individual decision accountabilities. The decision route for each case study was drafted using the structures in Oxera (2000), mapping the flow of evidence and noting the role played by various actors.

2.3. In-depth interviews

Semi-structured interviews (n = 3) were then conducted with experts for each case study to validate the decision routes above. Experts' feedback improved early drafts and validated the formal exchange of evidence between provider and recipient agents (Fig. 1). During the exploratory interviews, it became clear the sufficiency of evidence was, in part, determined by how it was characterised by six factors. Accordingly, the experts were asked to break decisions down into constituent phases on a timeline, and rate the extent to which the evidence could be characterised as being qualitative, quantitative, political, social, technical and costly. Information was used to construct the subsequent two-agent model.

2.4. Representing lines of evidence

The evidence used to test a hypothesis about the significance of a risk and how it should be managed is rarely uniform in direction, strength or weight (see Linkov et al., 2009). Evidence is frequently nested, in that evidence supporting a high-level 'parent' hypothesis is often contingent on lower level 'child' hypotheses with their associated lines of evidence. To represent this structure, we employed the TESLA™ software (http://www.quintessa-online.com/TESLA/; Benbow et al., 2006; Quintessa, 2008). TESLA adopts evidence supporting logic and interval probability theory to represent how lines of evidence inform a group decision; say, on the risks of radioactive release from a waste repository over time (Fig. 2). TESLA disaggregates a decision into a hierarchy of parent and child hypotheses, for which an expert group – reflecting on how sufficient and necessary a child hypothesis is for answering a corresponding parent – determines the influence the available evidence has. In this way, 'degrees of belief' that support (+) or refute (−) a parent hypothesis are constructed, with uncommitted belief also being captured (Fig. 2), the sum of these weights equating to 1 (100% belief).

Adapting TESLA, we assumed each hypothesis has an agent — a recipient with responsibility for interrogating the evidence submitted to them. Regulatory staff in different positions of authority has variable degrees of power to determine the sufficiency and adequacy of evidence submitted in support of a belief — say about the operational safety of an industrial facility.

2.5. A deterministic two-agent model incorporating receptivity

A two-agent model to simulate the understanding above was developed using North and Macal (2007). Receptivity facilitates knowledge sharing (Deng, 2007; Wang et al., 2008, 2009) and the opposite of receptivity is resistance (Kearney, 2007). Agent receptivity was represented through the assignment of weights (see Appendix A for conditional logic) for personality and power influences (Davies et al., 2010), and for the receipt, processing and passing-on of evidence, with an overall receptivity weight derived. An interface allowed the user to vary the conditions for the recipient's receptivity for a set of scenarios (see Supplementary Information Table A1 and Fig. A1). Spreadsheet layers, represented in Fig. 3, drew on values set through the interface and performed 10 000 runs for recipients' receptivity under selected scenarios. The mean receptivity (with standard deviation) was estimated using three steps:

1. Intensity ranges were assigned to factors (personality and power, and the level of decision uncertainty) that influenced recipient receptivity.
2. The model selected values at random within these ranges using the random number generator within MS Excel®.
3. Values (0–1) were propagated through the receptivity model to generate a weight for the receipt, processing and passing-on stages, before being averaged to generate an overall recipient receptivity.

Levels of intensity were selected for agents' personality traits. The 'big five' traits (openness, conscientiousness, extroversion, agreeableness and neuroticism) said to represent the most stable characteristics of individuals over time were employed, with 'neuroticism' replaced

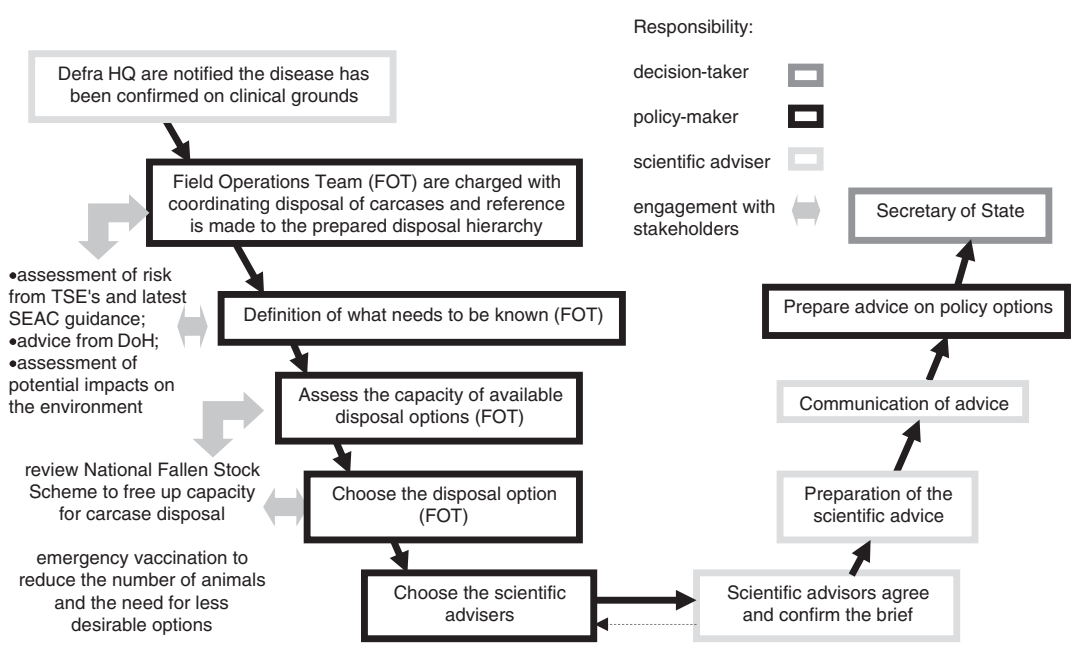

Fig. 1. Example decision route for the disposal of avian influenza (AI) infected carcasses, having validated the flow and exchange of evidence between 'provider' and 'recipient'. Ultimate decision-maker is shown as Secretary of State (SoS; Davies, 2010), where TSE, SEAC and DoH refer to 'Transmissible Spongiform Encephalopathy', 'Spongiform Encephalopathy Advisory Committee' and Department of Health respectively.

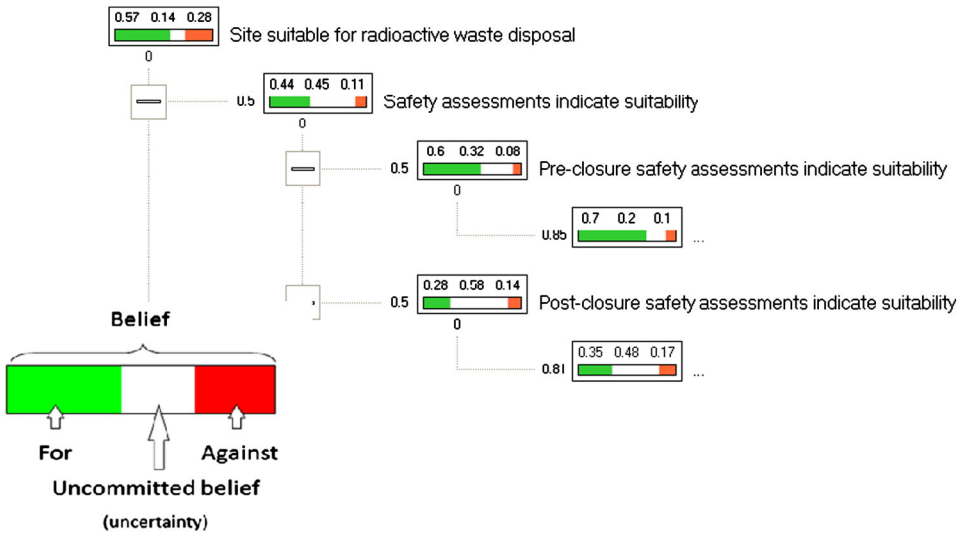

Fig. 2. TESLA representation of parent and child hypotheses for radioactive waste disposal. Adapted from Quintessa, 2008.

by 'emotional stability' (the reverse of 'neuroticism') allowing a scoring of traits uniform in direction (Johnson, 1999; Costa and McCrae, 1992). Scholars scoring personality traits do so on a scale from 0 to 100, agreeing that scores 55 or higher are considered to exhibit a strong dimension in that trait. Those that score 45 or below are considered to exhibit the opposite effect. Trait scores between 45 and 55 fall within the standard deviation of the big five personality test (Barrick et al., 1998; Digman, 1990; Ghasem-Aghaee and Ören, 2007; Hodson and Sorrentino, 1999). Trait scores were assigned for recipient and provider, representing agent's motivation to process information systematically and to share this knowledge (Davies et al., 2010; Hodson and Sorrentino, 1999). Here, the conventional degrees of intensity (low,

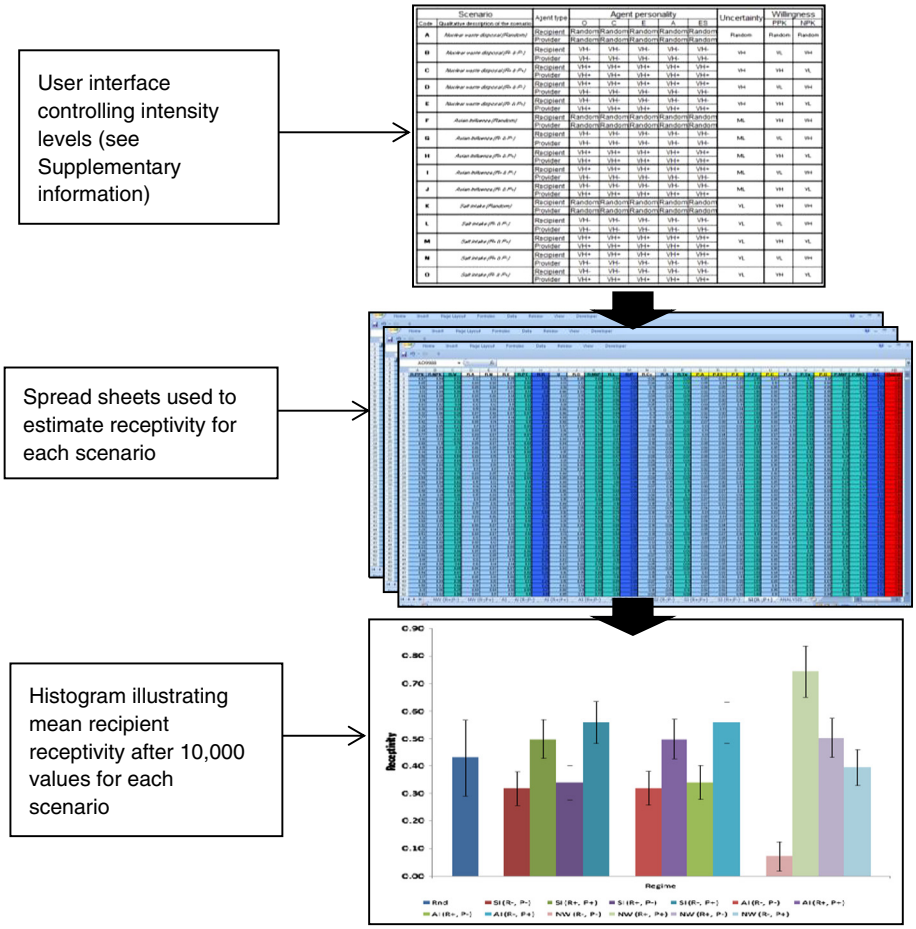

Fig. 3. Logical flow of the deterministic two-agent model.

Table 2
(a, b) Levels of intensity characterising (a) decision uncertainty; and (b) personality trait, where "Random" refers to the option to select values using a random number generator.

(a) Levels of intensity used to characterise decision uncertainty.	
Very high (VH)	0.83 to 0.99
High (H)	0.66 to 0.82
High medium (HM)	0.50 to 0.66
Low medium (LM)	0.33 to 0.50
Low (L)	0.17 to 0.33
Very low (VL)	0 to 0.16
Random	0 to 0.99
(b) Levels of intensity used to characterise each personality trait.	
Very high (VH)	0.775 to 1
High (H)	0.55 to 0.775
High medium (HM)	0.50 to 0.55
Low medium (LM)	0.45 to 0.50
Low (L)	0.225 to 0.45
Very low (VL)	0 to 0.225
Random	0 to 1

medium and high) were refined to six levels to investigate the influence of decision uncertainty (Table 2a, b). This allowed the user to better represent the case studies by low to high levels of decision uncertainty.

2.6. A dynamic two-agent model incorporating personality and power

Finally, we attempted a dynamic version of the model to incorporate a two-way interaction (dialogue) between provider and recipient and explore the confidence that might be instilled in recipients about the adequacy of evidence submitted to them. In interviews, experts explained how recipients and providers negotiate and reach consensus about the adequacy of evidence. We were interested whether the model could represent this process. Agent receptivity in the dynamic model was represented using the logic set out in the deterministic model, although three rather than six levels of intensity were used. Legitimate power and referent power were also incorporated. Legitimate power reflects the limited period recipients that are permitted to engage with providers. The model assumed a consultation consisted of one submission of evidence per day. The number of days' consultation was set by the value of the recipient's legitimate power, which decreased by a value of '1' with each simulation run. Referent power was reflected by including this within agent's assessment of receptivity. An agent's referent power was assessed by taking the average of the agent's agreeableness and emotional stability.

Using suitable combinations of the 'big five' personality traits above, agents were assigned one of four personalities ('negotiator', 'aggressor', 'submissive' and 'avoider'; Nassiri-Mofakham et al., 2008, 2009; Santos et al., 2010). To achieve this, each of the big five personality traits, for each agent, was assigned a low, medium or high value (0–0.45, 0.45–0.55 and 0.55–1 respectively). Because the literature does not specify for certain the intensity for the four personality sets, a level of intensity was selected from a uniform distribution and maintained within this band for subsequent simulations, as illustrated in Table 3 for the "Agent environment" spread sheet.

Visual Basic for Applications (VBA) code was used to update an "Agent environment" spread sheet according to changes in the agents' personal information in the model (Fig. 4) and contextual issues derived from a "Scenario" spread sheet; before receptivity was estimated and stored in a "Data log" spread sheet. For every run, a new random value was generated within the same band for each personality trait. Updating the recipient's and provider's personal information (Fig. 4) reflected the variance in the expression of personality across different decision contexts (Costa and McCrae, 1992). Overall receptivity was estimated using an average of receptivity across each of the three stages — the receiving, processing and passing-on stage of evidence brokering.

The model dynamics incorporated four stages simulating the transaction of evidence from provider to recipient (Fig. 5). The extent to which a transaction is successful depended on how the evidence was characterised by the parties (qualitative, quantitative, political, social, technical and costly aspects). If the recipient and provider expectations match, the brokering is successful and the recipient's confidence in the 'trade' builds.

The provider submitted evidence in support of their belief, and the recipient evaluated the adequacy of the evidence, their confidence in it and thereby the sufficiency of the provider's belief (Fig. 5, stage 1). Where these matched, the recipient was considered to have 100% confidence in the trade. Where there was a mismatch (Fig. 5, stage 2), these weights were multiplied against the recipient's weights and the ratio between new and the initial sum of recipients weights subtracted from the value of 1 (100%) and multiplied by one hundred to represent recipients increased confidence in the adequacy of evidence. If the recipient had legitimate power and the evidence failed to instil the recipient with 100% confidence, the recipient would engage in consultation with the provider. The evidence was passed back to the provider; a corollary of a request for additional information or further work from a regulatee (Fig. 5, stage 3). Taking the average of the recipient's receptivity and the provider's receptivity indicated how likely the provider would be to understand the expectations of the recipient (Fig. 5, stage 4). If this value fell between 0.15 & 0.38, 0.38 & 0.57 or 0.57 & 0.92 then the provider was considered to have a low, medium or high chance (respectively) of understanding how the recipient's expectations. This was expressed in the model by generating a random value for each aspect of the evidence between 0 & 1, 0.33 & 1 or 0.66 & 1 respectively; allowing the provider a greater chance of weighting the evidence adequately. This random value was generated within the specified range for each type of evidence characterising the new submission. These were then multiplied against the remaining weights that the recipient had assigned to each types of evidence before recalculating recipients confidence. This represented the extent to which a new submission would meet the recipient's expectations. If the recipient had legitimate power and the new submission of evidence failed to instil 100% confidence, the recipient would engage in further consultation with the provider (Fig. 5, go around the loop again) until they lacked legitimate power to do so or were 100% confident in the adequacy of the submitted evidence. This process was captured in a series of subroutines called up in a logical order (see Supplementary Information Figs., A2 & 3, Table A2). An iteration of evidence between recipient and provider was allowed to continue until a 'Do While/Loop' function in VBA determined

Table 3
Showing relative levels of intensity (low, medium and high) assigned to each personality, where "Random" refers to the option to select a value at random between 0 and 1 using the MS Excel® random number generator.

Personality	Big five personality traits				
	Openness	Conscientiousness	Extroversion	Agreeableness	Emotional stability
Negotiator	Random	Medium	High	Medium	Medium
Aggressor	Random	High	High	Medium	Medium
Submissive	Random	Low	Low	Medium	Medium
Avoider	Random	Low	Low	Random	Low

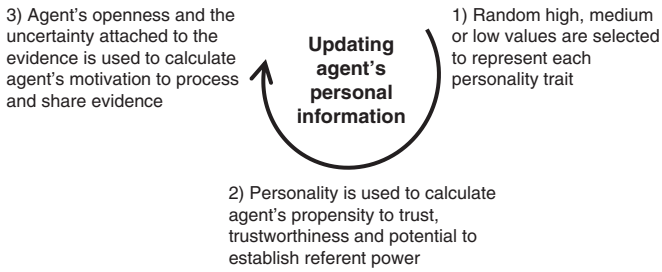

Fig. 4. Sequence of events for updating agents' receptivity according to changes in personal information.

the number of simulations were complete (representing the extent of the recipient's legitimate power).

3. Results

We present three sets of results: (i) recipient agents' receptivity as represented in the deterministic model; (ii) how agent personality differs in its predisposition towards 'propensity to trust', 'trustworthiness', 'motivation to process evidence' and 'motivation to share knowledge' which are used to represent agent receptivity; (iii) demonstrating how recipient and provider agents with greatest and least capacities to build receptivity also express greatest and least capacities to build confidence.

3.1. Recipient receptivity to evidence submitted

Fig. 6 illustrates how the recipient and provider have either a positive or a negative impact on the recipient's receptivity to a provider's belief, as supported by the evidence they submit. Each bar represents a mean of 10,000 recipient receptivity values, for 13 scenarios across the three case studies. Moving from left to right (Fig. 6), the first bar represents the control where intensity levels were randomly set between 0 and 1. Each subsequent cluster of four bars represents the low, medium and high levels of decision uncertainty and legitimate power for the salt intake (SI), carcase disposal (AI) and radioactive waste (RW) case studies, in turn. Bars within each cluster represent the recipient's receptivity under the following conditions:

- (dotted bar) both recipient and provider agents are set to have a negative impact on recipient's receptivity (R−& P−);

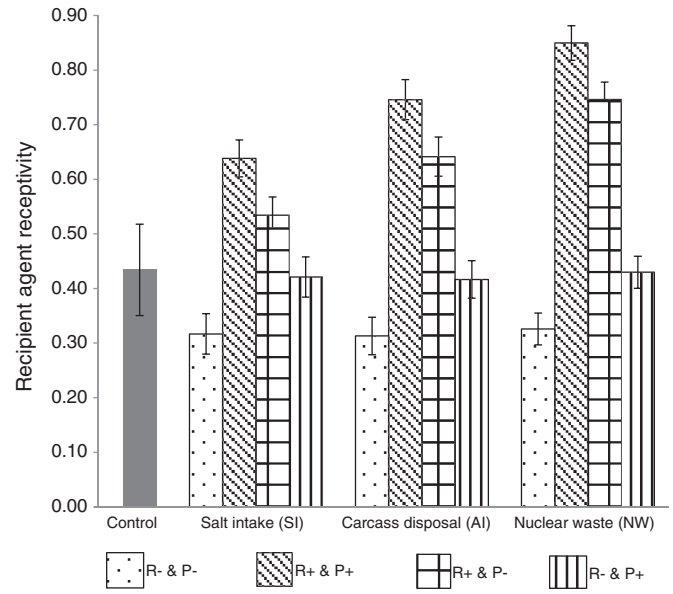

Fig. 6. Mean recipient's receptivity for 13 scenarios, with error bars representing standard deviation.

- (hashed bar) both recipient and provider agents are set to have a positive impact on recipient's receptivity (R+ & P+);
- (net) recipient and provider agent are set to have a negative and positive impact on recipient's receptivity, respectively (R+ & P−); and
- (vertical stripe) recipient and provider agents are set to have a positive and negative impact on recipient's respectively (R+ & P−).

The error bars represent standard deviation and show the difference between the mean receptivity when values for each parameter were selected at random between 0 and 1 (the control) and the mean receptivity in the situation where both the recipient and the provider were predisposed towards imbuing the recipient with receptivity (the second bar in each cluster). In all clusters, the recipient is seen to have the greatest impact on recipient receptivity, by comparing the third and fourth bars in each cluster. Also, the influence agents have on recipient receptivity increases with the presence of decision uncertainty, reflecting the impact of agent's motivation to process and share knowledge.

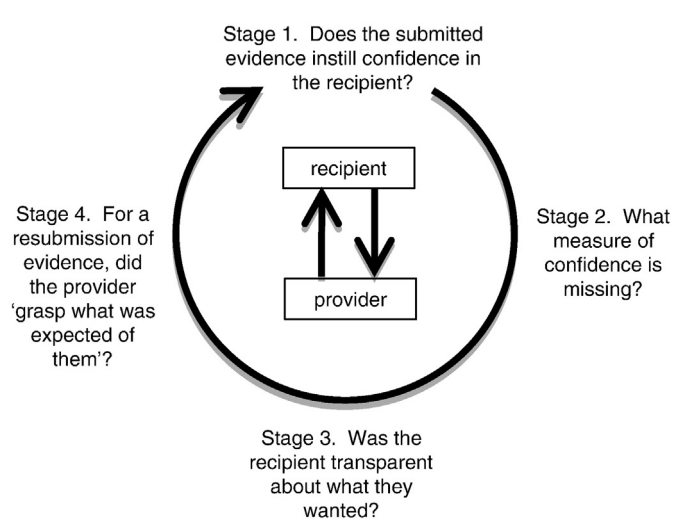

Fig. 5. Logic for the confidence building exercise with questions asked by the agent-based model sequentially in a clockwise order.

3.2. The dynamic model — the role of personality

Four personality sets were investigated; the 'negotiator', 'aggressor', 'submissive' and 'avoider'. These gave a broad indication of the model's capacity to simulate agent receptivity. The 'avoider' personality was split into avoider—low and avoider—high referring to high and low measures of agreeableness respectively, testing the model's capability to represent an agents' propensity to trust and trustworthiness. Fig. 7a–c illustrates that the avoider—low personality, with a low measure of agreeableness, produced the least propensity to trust and trustworthiness.

Fig. 8 illustrates the frequency of weights being generated over 10,000 runs under the best and worst circumstances for agents motivated to process and share knowledge. Agents' motivation to process knowledge was dependent on their orientation towards uncertainty (Hodson and Sorrentino, 1999). Agents with high levels of openness are uncertainty-motivated. Agents low in openness were said to be certainty-orientated. This meant that when uncertainty and openness were either both high or both low, they were motivated to process knowledge. An agent's motivation to share knowledge, however, was dependent on how motivated agents were to process the evidence. If either agent was highly motivated to process the evidence (or both were unmotivated), this resulted in agents being poorly motivated to share knowledge. If agents were unequally motivated to process the evidence they were more motivated to share knowledge (Cheng et al., Unpublished).

These results reflect the literature on the propensity to trust, trustworthiness and referent power. Table 4 shows that the aggressor and the avoider—low personality generated greatest and least propensities to trust, trustworthiness and referent power respectively.

Fig. 9 shows the different rates at which confidence was gained as recipients and providers engaged in dialogue under the best (top schematics; a) and worst (bottom schematics; b) case scenarios. At the onset of dialogue, the level of recipient's confidence varies, just as the rate at which confidence is attained varied for each submission. Even with this element of uncertainty, the model is able to distinguish between the best and worst case scenarios over 10 submissions of evidence (where the recipient must gain 100% confidence in the adequacy of supporting evidence before fully accepting the sufficiency of the providers' belief, and where recipients have unlimited legitimate power). The distinction between agents with personalities predisposed to being receptive and imbuing others with receptivity (and those that are not) is seen to affect the rate of the confidence building by: the rate at which the recipient's confidence builds over time, resulting in 10 submissions being completed in 71 rather than 96 days (i.e. 26% more efficient).

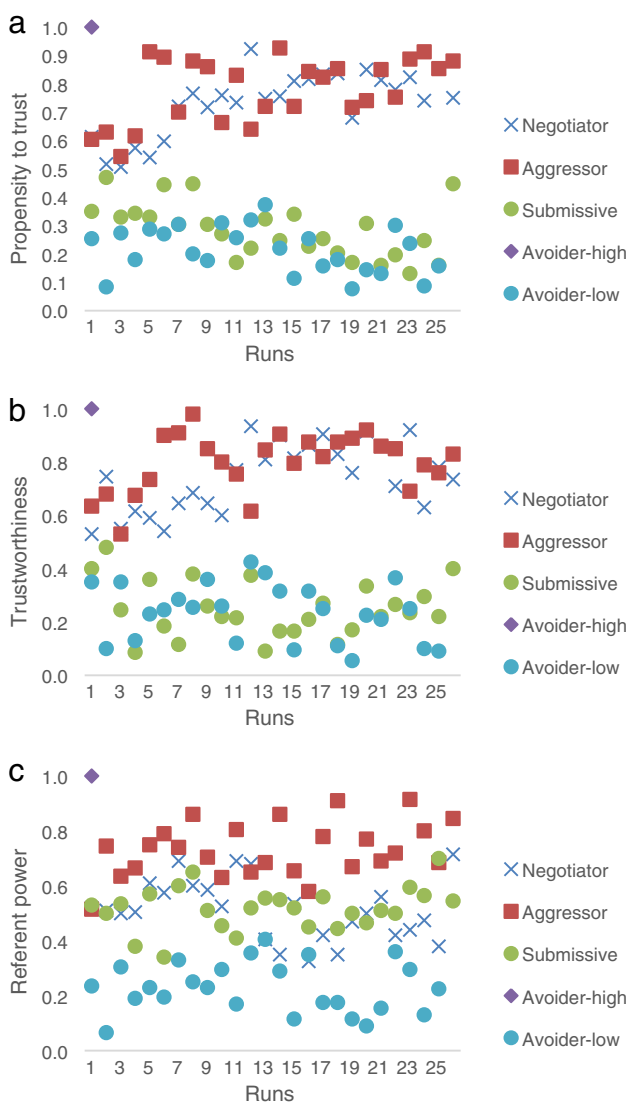

Fig. 7. Showing relative measures of (a) propensity to trust, (b) trustworthiness and (c) referent power for each of the four personalities in the two agent model where 'avoider—high' and 'avoider—low' personality is being calculated with high and low measures of agreeableness and emotional stability respectively.

4. Discussion

The nature of regulation is under review as western Governments move towards a more facilitative, decentralised approach (Gunningham, 2009; Gouldson et al., 2009). This raises issues about the tone of regulatory exchange, the quality of evidence that supports environmental risk decisions and the skill sets required of regulatory staff. For the regulated, the same applies — those seeking earned recognition by going beyond compliance (Taylor et al., 2012, 2013) need a new style of exchange. So how evidence is brokered, by whom, and under what conditions matters for beneficial regulatory, business and environmental outcomes. Using conventional approaches to ethnographic research with the intent of observing regulator–regulatee interactions up close is rarely practical. Agent-based approaches may have merit in revealing the influences at work when evidence to support decisions is provided to regulators, discussed and its suitability for informing decisions considered.

Classically, agent-based models focus on how complex dynamics and outcomes rely on the network of interactions between agents. They have been built using techniques such as discrete event simulation and object orientated programming (Brailsford and Schmidt, 2003) that reproduce the critical features of complex systems using component level rules. 'Behavioural signatures' can be allocated to individual agents (Epstein, 2006; North and Macal, 2007) offering a social richness and behavioural realism (Mischel, 1999; Mischel and Shoda, 1995; Shoda, 1999; Shoda et al., 2002) difficult to capture in

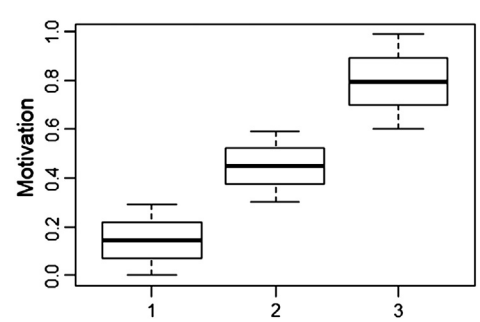

Fig. 8. Boxplots showing low (1), medium (2) and high (3) values generated for motivation to process evidence and motivation to share knowledge.

Table 4
Personalities that generate the 'most' and the 'least' propensity to trust, trustworthiness and referent power.

		Personality			
		Negotiator	Aggressor	Submissive	Avoider-low
Propensity to trust	'Most'	√	√		
	'Least'				√
Trustworthiness	'Most'		√		
	'Least'				√
Referent power	'Most'	√	√	√	
	'Least'				√

conventional decision analytics. Our two-agent model is rudimentary, but suggests how transactions between parties might influence a recipient's receptivity towards the evidence that subsequently informs a decision on risk. The two-agent model is shown capable, at least in principle, of exploring a recipient's tendency to trust, and the influence this has on their receptivity and the rate at which confidence can be gained.

To demonstrate the breadth of behaviour captured within the deterministic model, the most optimistic and pessimistic scenarios were simulated by making changes in system parameters; revealing the influence underlying features had on agent receptivity. As a form of validation, this was carried out for a number of scenarios, illustrating how the model reflects aspects of environmental permitting (NW), policy development (SI) and emergency planning decisions (AI). Recipient receptivity was highest for the former, which was expected given the greater level of uncertainty. Agents with high openness to experience providing evidence (characterised by high uncertainty) to agents with low openness to experience had high and low motivations to process information, respectively, and were highly motivated to share knowledge (Cheng et al., Unpublished; Hodson and Sorrentino, 1999; Sorrentino et al., 1992). It is also seen that recipient receptivity had a greater influence than provider receptivity (Fig. 6), suggesting the hierarchical model of receptivity is able to represent some of the trends explained to us by experts.

Model dynamics were developed by assigning agents specific personalities and drawing parallels between the brokering of evidence and that of commodities on a financial market. Agents wishing to exchange a commodity (here, confidence) must determine whether bids for the commodity are acceptable (i.e. whether provider and recipient expectations about the weight of evidence relevant to the decision are matched). Eventually, when the buyer (provider) makes an acceptable bid (a submission of adequately weighted evidence), the seller (recipient) exchanges the commodity for a specified currency (here, confidence translating into units of sufficiency about the evidence submitted to them). Accounting for the provider's receptivity is an important extension of the deterministic two agent model. Experts in the interviews explained how inexperienced regulatees (providers) may miss opportunities, during regulatory exchange, to instil recipient regulators with confidence by failing to communicate the weight of evidence supporting a risk decision — instead, evidence was presented in binary terms. Our model interpreted the provider's receptivity as the extent to which the agent would 'grasp what was being asked of them' through the regulatory exchange (Fig. 9). Similarly, Gratch et al. (2009) show how recipients engaging in intelligible conversation have a better chance of imparting knowledge. This understanding of recipient and provider receptivity was employed in our model to determine the likelihood that (1) recipients would openly divulge how they wanted the evidence to be weighted; and (2) that the provider would comprehend this.

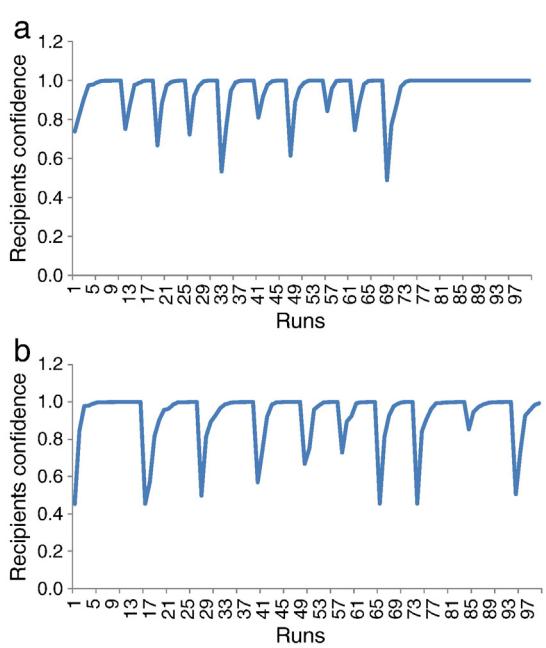

Fig. 9. (a, b). Confidence gained over multiple submissions of evidence (a) where both recipient and provider agents' personalities are predisposed to being receptive; and (b) where both are not predisposed to being receptive.

By giving agents sets of personality characteristics we showed that overall, the aggressor and the avoider personality had the greatest and least potential to influence agent receptivity. The 'avoider' personality set built confidence at a slower rate than the 'aggressor'; the latter suggesting the recipient personality set was less open to divulging what types of evidence they require, and for the provider suggesting a personality set less attentive to what was being asked of them. The pessimistic scenario, represented an agent that would not seek out engagement with a provider, compared to the optimistic scenario representing an agent that would. In Fig. 9a & b this is shown to affect the rate of confidence building. Whilst this succeeds in demonstrating the extremes of the dynamic model, we are not suggesting the 'aggressor' personality set is the ideal for all recipient transactions.

In the dynamic model the rate at which the regulator's confidence increased with time influenced confidence building. Experts told us that the rate of confidence building also varied for the three case studies. In the radioactive waste case, confidence would build at a slower rate because of the greater level of uncertainty characterising the decision. In our model this was mostly reflected by the influence of an agent's motivation to process and share knowledge between the pessimistic and the optimistic scenarios.

Having demonstrated a 'proof of concept' two-agent model, we believe it possible to develop a fully-fledged multi-agent system for the full set of interactions in Fig. 1, say. This would allow us to fully map the decision processes that have been validated by the experts and create 'behavioural signatures' to distinguish between agents in different positions within each decision hierarchy (see Mischel, 1999; Mischel and Shoda, 1995; Shoda, 1999; Shoda et al., 2002). Moreover, we have not fully explored the use of dependency in TESLA™. By applying the concept of dependency during the exchange of evidence, we might allow agents to evaluate new evidence only, making the transaction more realistic.

5. Conclusions

This paper demonstrates that it is possible to construct a two-agent model to reflect authentic regulatory situations, personality influences and power structures on information flows. Existing risk frameworks pay little homage to the reality that decisions are made by people, and as such, frameworks can fail to account for the influence power and personality may have on the brokering of evidence that supports decisions about risk (Powell, 1999). Here, an exploratory research tool capable of mapping the logic of how evidence is brokered, and confidence built, was developed. Simulation of personality sets

generating the greatest and the least agent receptivity (and thereby for building confidence) in this model was found to be the 'aggressor' and 'avoider' personalities. Comparing the most optimistic and pessimistic scenarios the former was able to complete 10 successful submissions in 71 days (compared with 96 days).

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Appendix A

Eqs. (1) and (2) were used to calculate agent receptivity. The values assigned to the personality traits (i.e. openness, conscientiousness, extroversion, agreeableness, emotional stability) depended in the personality assigned to the agent.

$$\text{R.Receptivity} = (\text{R.PtT} + \text{R.MtP} + \text{P.Tw} + \text{P.RP})/3 \quad (1)$$

$$\text{P.Receptivity} = (\text{R.Tw} + \text{R.RP} + \text{P.PtT} + \text{P.MtP} + \text{R.Mts})/4 \quad (2)$$

where:

$$\text{R.PtT} = (\text{RE} + \text{RA} + \text{RES})/3$$
$$\text{R.Tw} = (\text{RC} + \text{RA})/2$$
$$\text{P.PtT} = (\text{PE} + \text{PA} + \text{PES})/3$$
$$\text{P.Tw} = (\text{PC} + \text{PA})/2$$
$$\text{P.RP} = (\text{PA} + \text{PES})/2$$
$$\text{R.RP} = (\text{RA} + \text{RES})/2$$

$$\text{R.MtP} = \begin{cases} 0.6 \le X \le 0.99 & \text{if}(\text{RO}>0.55 \text{ and } \text{Unc}>0.6) \text{ or } (\text{RO}<0.45 \text{ and } \text{Unc}<0.29) \\ 0 \le X \le 0.29 & \text{if}(\text{RO}>0.55 \text{ and } \text{Unc}<0.29) \text{ or } (\text{RO}<0.45 \text{ and } \text{Unc}>0.6) \\ 0.3 \le X \le 0.59 & \end{cases}$$

where $X \in \mathbb{R}$

$$\text{P.MtP} = \begin{cases} 0.6 \le X \le 0.99 & \text{if}(\text{PO}>0.55 \text{ and } \text{Unc}>0.6) \text{ or } (\text{PO}<0.45 \text{ and } \text{Unc}<0.29) \\ 0 \le X \le 0.29 & \text{if}(\text{PO}>0.55 \text{ and } \text{Unc}<0.29) \text{ or } (\text{PO}<0.45 \text{ and } \text{Unc}>0.6) \\ 0.3 \le X \le 0.59 & \end{cases}$$

where $X \in \mathbb{R}$

$$\text{R.MtS} = \begin{cases} 0.6 \le X \le 0.99 & \text{if}(\text{R.MtP}<0.29 \text{ and } \text{P.MtP}>0.6) \text{ or } (\text{R.MtP}>0.6 \text{ and } \text{P.MtP}<0.29) \\ 0 \le X \le 0.29 & \text{if}(\text{R.MtP}<0.29 \text{ and } \text{P.MtP}<0.29) \text{ or } (\text{R.MtP}>0.6 \text{ and } \text{P.MtP}>0.6) \\ 0.3 \le X \le 0.59 & \end{cases}$$

where $X \in \mathbb{R}$

where:

R.PtT	Recipient's propensity to trust
R.MtP	Recipient's motivation to process knowledge
P.Tw	Propensity to trust
R.Tw	Recipient's trustworthiness
P.PtT	Provider's propensity to trust
P.MtP	Provider's motivation to process knowledge
R.Mts	Recipient's motivation to share knowledge
RE	Recipient's extroversion
RA	Recipient's agreeableness
RES	Recipient's emotional stability
R.Tw	Recipient's trustworthiness
RC	Recipient's conscientiousness
RA	Recipient's agreeableness
P.PtT	Provider's propensity to trust
PE	Provider's extroversion
PA	Provider's agreeableness
PES	Provider's emotional stability
P.Tw	Provider's trustworthiness
PC	Provider's conscientiousness
PA	Provider's agreeableness
RO	Recipient's openness
PO	Provider's openness
Unc	Decision uncertainty
P.RP	Provider's referent power
R.RP	Recipient's referent power.

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.scitotenv.2013.06.116.

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